ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM FOR COMPUTING THE RESONANT FREQUENCY OF CIRCULAR MICROSTRIP ANTENNAS

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ABSTRACT: A new method for computing the resonant frequency of the circular microstrip antenna, based on the adaptive neuro-fuzzy inference system (ANFIS), is presented. A hybrid learning algorithm is used to identify the parameters of ANFIS. The results of the new method are in excellent agreement with the experimental results reported elsewhere.

1. INTRODUCTION

Microstrip antennas (MSAs) have many attractive features such as low profile, light weight, ease of manufacture, conformability to curved surfaces, low production cost, and compatibility with integrated circuit technology [1-5]. These attractive features have recently increased the application of MSAs and stimulated greater effort to investigate their performances. MSAs have been used in various configurations: square, rectangular, circular, triangular, trapezoidal, elliptical etc. Circular microstrip patches can be used as resonant antennas, and also as planar resonators for oscillators and filters in microwave integrated circuits. In circular MSA designs, it is important to determine the resonant frequencies of the antenna accurately because MSAs have narrow bandwidths and can only operate effectively in the vicinity of the resonant frequency. Thus, a model to determine the resonant frequency is helpful in antenna designs. Several methods [1-29], varying in accuracy and computational effort, have been proposed and used to calculate the resonant frequency of circular MSAs. These methods can be broadly classified into two categories: analytical and numerical methods. The analytical methods, based on some fundamental simplifying physical assumptions regarding the radiation mechanism of antennas, are the most useful for practical designs as well as for providing a good intuitive explanation of the operation of MSAs. However, these methods are not suitable for many structures, in particular, if the thickness of the substrate is not very thin. The numerical methods are mathematically complex, take tremendous computational efforts, still can not make a practical antenna design feasible within a reasonable period of time, require strong background knowledge and have time-consuming numerical calculations which need very expensive software packages. So, they are not very attractive for the interactive computer aided design (CAD) models. In general, the numerical methods are based on an electromagnetic boundary problem, which leads to expression as an integral equation, using proper Green's function, either in the spectral domain, or directly in the space domain, using moment methods. Without any initial assumption, the choice of test functions and the path integration appear to be more critical during the final, numerical solution. The numerical methods also suffer from the fact that any change in the geometry (patch shape, feeding method, addition of a cover layer, etc.) requires the development of a new solution. Furthermore, the theoretical resonant frequency results calculated from the curve-fitting formulas [18], [21] based on the rigorous numerical methods are not in good agreement with the experimental results [6], [8], [11], [14-17]. However, the results of these curve-fitting formulas are in very good agreement with the results of numerical methods [1-5].

In this paper, a new method based on the adaptive neuro-fuzzy inference system (ANFIS) [30], [31] is presented to calculate accurately the resonant frequencies of the circular MSAs. First, the antenna parameters related to the resonant frequencies are determined, and then the resonant frequencies depending on these parameters are calculated by using the ANFIS. The ANFIS is a class of adaptive networks which are functionally equivalent to fuzzy inference systems (FISs). It combines the powerful features of FISs with those of artificial neural networks (ANNs). A hybrid learning algorithm [30, 31], which combines the least-square method and the backpropagation algorithm, is used to determine optimally the values of ANFIS parameters. Fast and accurate learning, excellent explanation facilities in the form of semantically meaningful fuzzy rules, the ability to accommodate both data and existing expert knowledge about the problem, and good generalization capability features have made neuro-fuzzy systems popular in recent years [30-34]. Because of these attractive features, the ANFIS in this paper is used to model the relationship between the parameters of the circular MSAs and the measured resonant frequency results.

In previous works [35-37], we successfully used ANFIS to calculate the resonant frequency of triangular MSAs and the input resistance of rectangular and circular MSAs. We also proposed FISs [38], [39] and ANNs [40-50] for computing

Report Documentation Page

Form Approved
OMB No. 0704-0188

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1. REPORT DATE **02 JUL 2004**	2. REPORT TYPE **N/A**	3. DATES COVERED **-**
4. TITLE AND SUBTITLE **Adaptive Neuro-Fuzzy Inference System For Computing The Resonant Frequency Of Circular Microstrip Antennas**		5a. CONTRACT NUMBER 5b. GRANT NUMBER 5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)		5d. PROJECT NUMBER 5e. TASK NUMBER 5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **Department of Electronics Engineering, Faculty of Engineering, Erciyes University, 38039, Kayseri, Turkey**		8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)		10. SPONSOR/MONITOR’S ACRONYM(S) 11. SPONSOR/MONITOR’S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release, distribution unlimited

13. SUPPLEMENTARY NOTES
See also ADM001760, Applied Computational Electromagnetics Society 2004 Archive., The original document contains color images.

14. ABSTRACT

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			
unclassified	**unclassified**	**unclassified**	**UU**	**10**	

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std Z39-18

accurately the various parameters of the rectangular, circular, and triangular MSAs, and pyramidal horn antennas. In the following sections, the resonant frequency of a circular MSA and the ANFIS are described briefly, and the application of ANFIS to the computation of the resonant frequency of a circular MSA is then explained.

2. RESONANT FREQUENCY OF A CIRCULAR MICROSTRIP ANTENNA

Figure 1 shows a circular patch of radius r_o over a ground plane with a substrate of thickness h and a relative dielectric constant ε_r. The resonant frequency of this circular MSA for the TM_{nm} mode is expressed as

$$f_{nm} = \frac{\alpha_{nm} c_o}{2\pi\, r_o \sqrt{\varepsilon_r}} \tag{1}$$

where α_{nm} is the mth zero of the derivative of the Bessel function of order n and c_o is the velocity of electromagnetic waves in free space. The dominant mode is TM_{11} (n = m =1), for which α_{11} =1.84118. Equation (1) is based on the assumption of a perfect magnetic wall and neglects the fringing fields at the open-end edge of the microstrip patch. Several suggestions have been presented in the literature [1-29] to account for these fringing fields. A survey of the literature [1-29] clearly shows that the resonant frequency of a circular MSA for TM_{11} mode strongly depends on r_o, h, and ε_r. Therefore, the effect of the size of the dielectric substrate is not considered in calculating the resonant frequency. In this work, the resonant frequency of the circular MSA is computed by using a method based on the ANFIS. Only three parameters, r_o, h, and ε_r, are used in calculating the resonant frequency.

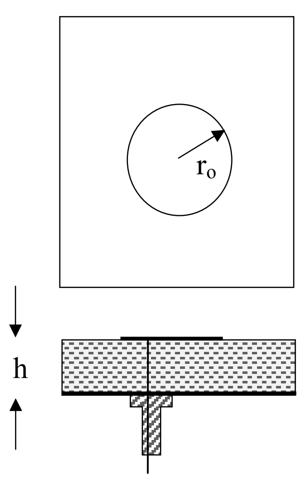

Fig. 1. Geometry of a circular microstrip antenna.

3. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

The ANFIS is a FIS implemented in the framework of an adaptive fuzzy neural network, and is a very powerful approach for building complex and nonlinear relationship between a set of input and output data [30], [31]. It combines the explicit knowledge representation of FIS with the learning power of ANNs. Usually, the transformation of human knowledge into a fuzzy system (in the form of rules and membership functions) does not give exactly the target response. So, the optimum values of the FIS parameters should be found. The main objective of the ANFIS is to determine the optimum values of the equivalent FIS parameters by applying a learning algorithm using input-output data sets. The parameter optimization is done in such a way that the error between the target and the actual output is minimized.

The ANFIS architecture consists of fuzzy layer, product layer, normalized layer, de-fuzzy layer, and summation layer. A typical ANFIS architecture is shown in Figure 2, in which a circle indicates a fixed node, whereas a square indicates an adaptive node. For simplicity, we assume that the FIS under consideration has two inputs x and y and one output z. The ANFIS used in this work implements a first-order Sugeno fuzzy model. Among many FIS models, the Sugeno fuzzy model is the most widely applied one for its high interpretability and computational efficiency, and built-in optimal and adaptive techniques. For a first-order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules can be expressed as

$$\textit{Rule 1: If } x \textit{ is } A_1 \textit{ and } y \textit{ is } B_1, \textit{ then } z_1 = p_1 x + q_1 y + r_1 \tag{2a}$$
$$\textit{Rule 2: If } x \textit{ is } A_2 \textit{ and } y \textit{ is } B_2, \textit{ then } z_2 = p_2 x + q_2 y + r_2 \tag{2b}$$

where A_i and B_i are the fuzzy sets in the antecedent, and p_i, q_i, and r_i are the design parameters that are determined during the training process. As in Figure 2, the ANFIS consists of five layers:

Layer 1: Every node i in this layer is an adaptive node with a node function:

$$O_i^1 = \mu_{A_i}(x), \qquad i = 1,2 \tag{3a}$$
$$O_i^1 = \mu_{B_{i-2}}(y), \qquad i = 3,4 \tag{3b}$$

where x (or y) is the input of node i. $\mu_{A_i}(x)$ and $\mu_{B_{i-2}}(y)$ can adopt any fuzzy membership function (MF). In general, the types of the MFs are determined by trial-and-error method and/or operator's experience. After this determination, the parameters of MFs and the number of fuzzy rules can be optimally obtained by using optimization techniques.

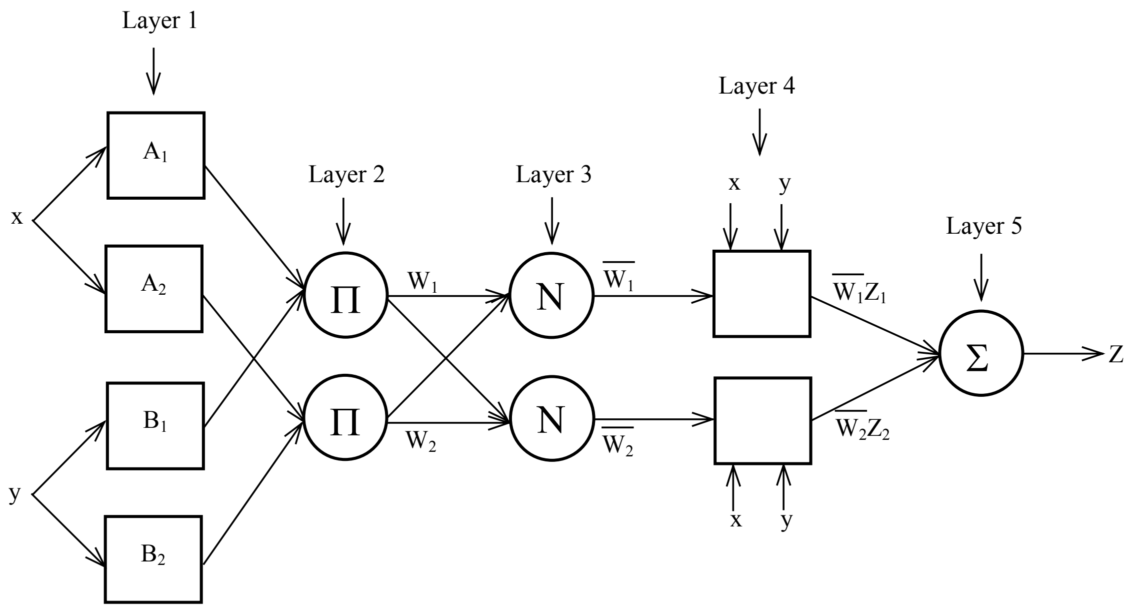

Fig. 2. Architecture of ANFIS.

In this paper, the following MFs are obtained by using trial-and-error methods:

i) Gaussian MFs

$$gaussian(x;c,\sigma)=e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2} \tag{4a}$$

ii) Triangular MFs

$$triangle(x;a,b,c)=\begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ \dfrac{c-x}{c-b}, & b \le x \le c \\ 0, & c \le x \end{cases} \tag{4b}$$

where $\{a_i, b_i, c_i, \sigma_i\}$ is the parameter set that changes the shape of the MF. Parameters in this layer are named *the premise parameters.*

Layer 2: Every node in this layer is a fixed node labeled Π, which multiplies the incoming signals and outputs the product:

$$O_i^2 = \omega_i = \mu_{A_i}(x)\mu_{B_i}(y), \qquad i = 1,2 \tag{5}$$

Each node output represents the firing strength of a rule.

Layer 3: Every node in this layer is a fixed node labeled N. The *i*th node calculates the ratio of the *i*th rule's firing strength to the sum of all rules' firing strengths:

$$O_i^3 = \overline{\omega_i} = \frac{\omega_i}{\omega_1 + \omega_2}, \qquad i = 1,2 \tag{6}$$

where $\overline{\omega_i}$ is referred to as *the normalized firing strength.*

Layer 4: Every node i in this layer is an adaptive node with a node function:

$$O_i^4 = \overline{\omega_i} z_i = \overline{\omega_i}(p_i x + q_i y + r_i), \qquad i = 1,2 \tag{7}$$

where $\overline{\omega_i}$ is the output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer are referred to as *the consequent parameters.*

Layer 5: The single node in this layer is a fixed node labeled Σ, which computes the overall output as the summation of all incoming signals:

$$O_1^5 = \sum_{i=1}^{2} \overline{\omega_i} z_i = \frac{\omega_1 z_1 + \omega_2 z_2}{\omega_1 + \omega_2}. \tag{8}$$

It can be seen from the ANFIS architecture that when the values of the premise parameters are fixed, the overall output can be expressed as a linear combination of the consequent parameters:

$$z=(\overline{\omega_1}x)p_1+(\overline{\omega_1}y)q_1+(\overline{\omega_1})r_1+(\overline{\omega_2}x)p_2+(\overline{\omega_2}y)q_2+(\overline{\omega_2})r_2. \tag{9}$$

The optimal values of the consequent parameters can be found by using the least-squares method (LSM). When the premise parameters are not fixed, the search space becomes larger and the convergence of training becomes slower. The hybrid learning algorithm combining the LSM and the backpropagation (BP) algorithm [51] can be used to solve this problem. This algorithm converges much faster since it reduces the dimension of the search space of the BP algorithm. During the learning process, the premise parameters in layer 1 and the consequent parameters in layer 4 are tuned until the desired response of the FIS is achieved.

The hybrid learning algorithm has a two-step process. First, while holding the premise parameters fixed, the functional signals are propagated forward to layer 4, where the consequent parameters are identified by the LSM. Then the consequent parameters are held fixed while the error signals, the derivative of the error measure with respect to each node output, are propagated from the output end to the input end, and the premise parameters are updated by the standard BP algorithm. The weight of each input variable to output is also determined by utilizing the hybrid-learning algorithm.

4. ANFIS FOR RESONANT FREQUENCY COMPUTATION

In this paper, the ANFIS has been used to calculate the resonant frequencies of circular MSAs. For the ANFIS, the inputs are r_o, h, and ε_r, and the output is the measured resonant frequencies f_{me}. The ANFIS model used in computing the resonant frequencies is illustrated in Figure 3.

There are two types of data generators for antenna applications. These data generators are measurements and simulations. The selection of a data generator depends on the application and the availability of the data generator. The training and test data sets used in this paper have been obtained from the previous experimental works published in seven sources [6], [8], [11], [14-17], and are given in Table 1. The 17 data sets in Table 1 were used to train the ANFIS. Three data sets, marked with an asterisk in Table 1, were used for testing. The values of electrical thickness, defined as h/λ_d where λ_d is the wavelength in the substrate, are also given in Table 1. The training and test data sets used in this paper are the same as those used for ANNs in [41], [47]. The antennas given in Table 1 vary in patch radius from 0.74 cm to 6.80 cm, and in physical thickness from 0.0794 cm to 0.318 cm, and operate over the frequency range 815 MHz - 6634 MHz.

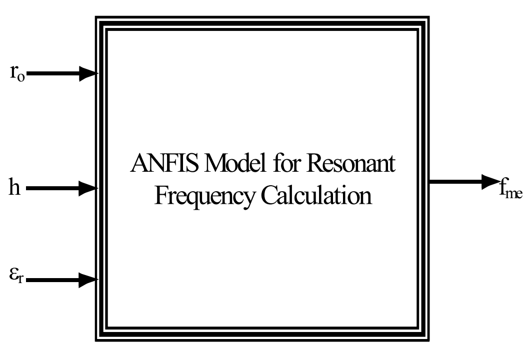

Fig. 3. ANFIS model for resonant frequency calculation.

Table 1. The measured resonant frequencies and the resonant frequencies obtained from the ANFIS proposed in this paper for circular microstrip antennas.

Patch No	r_o (cm)	h (cm)	ε_r	h/λ_d	Measured f_{me} (MHz)	Present ANFIS Method (MHz)
1	6.800	0.08000	2.32	0.003392	835$^{\square}$	835
2*	6.800	0.15900	2.32	0.006692	829$^{\square}$	832
3	6.800	0.31800	2.32	0.013159	815$^{\square}$	815
4	5.000	0.15900	2.32	0.009106	1128$^{\Delta}$	1128
5	3.800	0.15240	2.49	0.011567	1443$^{\nabla}$	1443
6	4.850	0.31800	2.52	0.018493	1099^{x}	1099
7	3.493	0.15880	2.50	0.013140	1570$^{\blacklozenge}$	1570
8	1.270	0.07940	2.59	0.017336	4070$^{\blacklozenge}$	4070
9	3.493	0.31750	2.50	0.025268	1510$^{\blacklozenge}$	1510
10	4.950	0.23500	4.55	0.013785	825	825
11	3.975	0.23500	4.55	0.017210	1030	1030
12*	2.990	0.23500	4.55	0.022724	1360	1360
13	2.000	0.23500	4.55	0.033468	2003	2003
14	1.040	0.23500	4.55	0.062659	3750	3750
15	0.770	0.23500	4.55	0.082626	4945	4945
16	1.150	0.15875	2.65	0.038118	4425†	4425
17	1.070	0.15875	2.65	0.040684	4723†	4723
18*	0.960	0.15875	2.65	0.045006	5224†	5225
19	0.740	0.15875	2.65	0.057146	6634†	6634
20	0.820	0.15875	2.65	0.052300	6074†	6074

$^{\square}$These frequencies are measured by Dahele and Lee [14]; $^{\Delta}$this frequency is measured by Dahele and Lee [15]; $^{\nabla}$ this frequency is measured by Carver [11]; ^{x} this frequency is measured by Antoszkiewicz and Shafai [17]; $^{\blacklozenge}$these frequencies are measured by Howell [8]; † these frequencies are measured by Itoh and Mittra [6]; the remainder are measured by Abboud et al. [16]. *Test data sets.

Training an ANFIS by using the hybrid learning algorithm to calculate the resonant frequency involves presenting it sequentially with different sets (r_o, h, ε_r) and corresponding measured values f_{me}. Differences between the target output f_{me} and the actual output of the ANFIS are evaluated by the hybrid learning algorithm. The adaptation is carried out after the presentation of each set (r_o, h, ε_r) until the calculation accuracy of the ANFIS is deemed satisfactory according to some criterion (for example, when the error between f_{me} and the actual output for all the training sets falls below a given threshold) or when the maximum allowable number of epochs is reached.

The number of epochs was 100 for training. The number of MFs for the input variables r_o, h, and ε_r are 8, 2, and 6, respectively. The number of rules is then 96 (8x2x6=96). The type of MF is gaussian for r_o and triangular for h and ε_r. It is clear from eq. (4) that the gaussian and triangular MFs are specified by two and three parameters, respectively. Therefore, the ANFIS used here contains a total of 424 fitting parameters, of which 40 (8x2+2x3+6x3=40) are the premise parameters and 384 (4x96=384) are the consequent parameters.

5. RESULTS AND CONCLUSIONS

The resonant frequencies computed by using ANFIS presented in this paper for different circular MSAs are listed in Table 1. For comparison, the results obtained by using the conventional methods [8], [10], [11], [16], [18-21], [24-27] and by using the neural models [41, 47] based on the multilayered perceptrons and the radial basis function networks are given in Tables 2 and 3, respectively. BP, EDBD, DBD, QP, DRS, GA, and RBFN in Table 3 represent, respectively, the resonant frequencies calculated by using multilayered perceptrons trained by backpropagation (BP) [51], extended delta-bar-delta (EDBD) [52], delta-bar-delta (DBD) [53], quick propagation (QP) [54], directed random search (DRS) [55], and genetic algorithms (GA) [56], [57], and calculated by using the radial basis function network (RBFN) [58-60] trained by EDBD algorithm. The sum of the absolute errors between the theoretical and experimental results in Tables 1, 2, and 3 for every method is also listed in Table 4.

In Table 2, the results of Carver [11] were obtained by using the modal expansion technique. The formula based on the cavity model with a perfect magnetic wall was used by Howell [8]. The accuracy of the cavity model can be improved by taking modal and fringing field effects into consideration. In [10], the results were determined from the combination of the effective patch radius formula suggested by Shen et al. [9] and the relative dielectric constant. Abboud et al. [16] computed the resonant frequencies by using the dynamic permittivity constant expression presented by Wolff and Knoppik [7] and the effective patch radius expression derived from the static fringing capacitance formula presented by Chew and Kong [12].

The resonant frequency can be obtained rigorously using the vector Hankel transform method [13] in terms of vector dual integral equations. This method is mathematically complex and requires high performance large-scale computer resources and a very large number of computations. For this reason, Liu and Chew [18] proposed a Fortran program of curve-fitting formula for the resonant frequency. This formula was obtained by using a database built by Galerkin's method, based on the formulation by Chew and Kong [13]. Close agreement was obtained between the results of the curve-fitting formula and the results of Galerkin's method. However, the results of the curve-fitting formula are not in very good agreement with the experimental results, as shown in Tables 2 and 4.

Roy and Jecko [19] calculated the resonant frequencies by using a curve-fitting formula based on the computed data of existing theory. For this formula, it is not necessary to compute the zeros of the derivative of the Bessel function, however, it is clear from Tables 2 and 4 that the results obtained from the formula are not in very good agreement with the experimental results. The results of Guney [20] were determined by using the effective values for both the patch radius and the substrate permittivity.

The moment-method is one of the most widely used methods in analyzing the performance of MSAs. This method is not practical as a quick antenna design aid because its computational cost is high due to the evaluation of the slowly decaying integrals and the iterative nature of the solution process. Because of this problem, Lee and Fan [21] presented the curve-fitting formulas based on the moment-method results. These relatively simple formulas allow designers to calculate the resonant frequencies for a given design without having to develop or run the moment-method code themselves. It was shown in [21] that the resonant frequencies predicted by the curve-fitting formulas agree well with the moment-method results. However, it is apparent from Tables 2 and 4 that the results of these formulas are not in very good agreement with the experimental results.

In [24], [25], the simple effective patch radius expressions obtained from the tabu search and genetic algorithms have been presented for calculating the resonant frequency. The tabu search and genetic algorithms were used to determine optimally the unknown coefficient values of the models chosen for the effective patch radius expressions.

Gurel and Yazgan [26] computed the resonant frequencies by using an effective patch radius expression combined with the proper effective permittivity formula. In order to improve the accuracy of the calculations in [26], a modified dynamic permittivity formula was also used by Gurel and Yazgan [27].

It can be clearly seen from Tables 2 and 4 that the conventional methods give comparable results. Some cases are in good agreement with measurements, and others are far off. The best result among conventional methods is obtained from the formulas proposed by Akdagli and Guney [25].

As it is seen from Tables 2, 3, and 4, the results of all neural models are better than those predicted by the conventional methods. These results clearly show the superiority of ANNs over the conventional methods. When the performances of neural models presented in [41], [47] are compared with each other, the highest accuracy was achieved with the ANN trained by the EDBD algorithm.

Table 2. Resonant frequencies obtained from conventional methods available in the literature [8, 10, 11, 16, 18-21, 24-27] for circular microstrip antennas.

Patch No	Measured f_{me} (MHz)	Conventional Methods in the Literature											
		[11]	[8]	[10]	[16]	[18]	[19]	[20]	[21]	[24]	[25]	[26]	[27]
1	835	845	849	840	842	844	838	841	840	843	840	842	839
2	829	842	849	833	837	839	831	836	832	838	831	837	833
3	815	834	849	821	826	829	819	826	818	828	815	827	824
4	1128	1141	1154	1127	1133	1136	1124	1132	1125	1135	1123	1133	1129
5	1443	1445	1466	1427	1436	1439	1423	1435	1423	1438	1432	1436	1431
6	1099	1115	1142	1098	1105	1109	1095	1105	1091	1107	1100	1107	1103
7	1570	1565	1580	1545	1555	1559	1541	1554	1539	1558	1550	1556	1550
8	4070	4203	4290	4145	4175	4187	4134	4173	4120	4183	4168	4179	4163
9	1510	1539	1580	1513	1522	1529	1509	1523	1498	1524	1510	1525	1520
10	825	818	833	818	827	827	816	825	817	824	823	827	823
11	1030	1014	1037	1016	1027	1027	1013	1026	1013	1024	1022	1028	1023
12	1360	1339	1379	1344	1358	1360	1340	1359	1336	1355	1352	1361	1355
13	2003	1972	2061	1990	2009	2012	1984	2012	1966	2007	2002	2015	2009
14	3750	3627	3963	3749	3744	3737	3739	3752	3634	3750	3750	3750	3751
15	4945	4722	5353	5001	4938	4922	4987	4943	4817	4948	4945	4932	4944
16	4425	4461	4695	4399	4413	4437	4388	4422	4328	4422	4413	4423	4415
17	4723	4776	5046	4712	4723	4749	4699	4731	4630	4730	4722	4733	4725
18	5224	5289	5625	5223	5226	5257	5209	5237	5121	5231	5224	5237	5231
19	6634	6733	7297	6679	6644	6684	6661	6658	6499	6634	6636	6652	6651
20	6074	6125	6585	6063	6047	6084	6046	6061	5920	6046	6043	6057	6054

Table 3. Resonant frequencies obtained by using artificial neural networks (ANNs) presented in [41, 47] for circular microstrip antennas.

Patch No	Measured f_{me} (MHz)	Artificial Neural Networks (ANNs) [41, 47]						
		BP	EDBD	DBD	QP	DRS	GA	RBFN
1	835	835	835	835	835	835	930	835
2	829	828	828	828	828	932	898	812
3	815	815	815	815	815	816	899	815
4	1128	1128	1128	1128	1126	1126	944	1129
5	1443	1443	1443	1443	1446	1443	1435	1440
6	1099	1099	1099	1099	1100	1098	1081	1099
7	1570	1570	1570	1570	1568	1572	1582	1572
8	4070	4070	4070	4070	4070	4070	4028	4070
9	1510	1510	1510	1510	1509	1510	1516	1510
10	825	825	825	825	826	828	885	826
11	1030	1030	1030	1030	1029	1024	1013	1029
12	1360	1361	1361	1364	1357	1362	1198	1399
13	2003	2003	2003	2003	2003	2007	1996	2004
14	3750	3750	3750	3750	3750	3747	3751	3749
15	4945	4945	4945	4945	4945	4947	4943	4946
16	4425	4425	4428	4425	4426	4413	4471	4427
17	4723	4723	4720	4723	4721	4732	4690	4719
18	5224	5233	5224	5232	5225	5261	5184	5230
19	6634	6634	6634	6634	6633	6617	6632	6630
20	6074	6074	6075	6074	6075	6094	6078	6080

Table 4. Sum of absolute errors between measured and calculated resonant frequencies.

Methods		Total absolute deviations from the measured data (MHz)
ANFIS	Present Method	4
Conventional Methods in the Literature	[11]	965
	[8]	3341
	[10]	337
	[16]	253
	[18]	383
	[19]	380
	[20]	253
	[21]	1047
	[24]	253
	[25]	207
	[26]	275
	[27]	235
Artificial Neural Networks (ANNs) [41, 47]	BP	11
	EDBD	9
	DBD	13
	QP	21
	DRS	224
	GA	892
	RBFN	89

It is evident from Tables 1-4 that the results of ANFIS show better agreement with the experimental results as compared to the results of the conventional methods [8], [10], [11], [16], [18-21], [24-27] and the ANN models [41], [47]. The excellent agreement between the experimental results and our computed resonant frequency results supports the validity of the ANFIS model proposed in this paper.

For accurately computing the various parameters of complicated antenna structures, the ANFIS can be used but it should be trained by using appropriate training data sets. The training data sets should contain desired input/output data pairs of the target antenna to be modeled. A prominent advantage of the ANFIS model is that, after proper training, ANFIS completely bypasses the repeated use of complex iterative processes for new cases presented to it. Even if training takes a few minutes, the test process takes only a few microseconds to produce the resonant frequency. ANFIS are also less susceptible to the noise inherent in measured data and antenna imperfections [61].

In the last decade, ANNs have been widely used to solve antenna and electromagnetic engineering problems as a fast, accurate, and flexible method [62], [63]. However, better results can be obtained by using the ANFIS in solving these problems because the ANFIS is a very effective modeling scheme combining the benefits of both ANNs and FISs in a single model. We expect that the ANFIS will find a wide application area in antenna and electromagnetic engineering as ANNs did.

In this study, the ANFIS is trained and tested with the experimental data taken from the previous experimental works [6], [8], [11], [14-17]. It is apparent from Tables 2 and 4 that the theoretical resonant frequency results of the conventional methods are not in very good agreement with the experimental results. For this reason, the theoretical data sets obtained from the conventional methods are not used in this work. Only the measured data set is used for training and testing the ANFIS. It also needs to be emphasized that better results may be obtained from the ANFIS either by choosing different training and test data sets from the ones used in the paper or by supplying more input data set values for training.

In this paper, only the lowest resonant frequency f_{11} for the TM_{11} mode is calculated by using the ANFIS because this circular microstrip patch mode is widely used in MSA applications. However, the ANFIS can be easily adapted to compute the resonant frequencies of higher-order modes of practical interest if the data sets for these modes are available. It must also be emphasized that the proposed ANFIS method is not limited to the resonant frequency calculation of circular MSAs. This method can be easily applied to other antenna and microwave engineering problems. Accurate, fast, and reliable ANFIS models can be developed from measured/simulated antenna data. Once developed, these ANFIS models can be used in place of computationally intensive numerical models to speed up antenna design.

As a result, the ANFIS trained by means of the measured data is presented to calculate accurately the resonant frequency of circular MSAs with substrates with $2.32 \leq \varepsilon_r \leq 4.55$ and 0.0794 cm $\leq h \leq 0.318$ cm. A hybrid learning algorithm is used to optimize the parameters of ANFIS. The results of ANFIS are in excellent agreement with the measurements, and better accuracy with respect to the previous conventional methods and neural models is obtained. The ANFIS offers an accurate and efficient alternative to previous methods for the calculation of the resonant frequencies.

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